VARIABLES IN CMP'S RESIDENTIAL SALES EQUATION

Introduction

In this section we describe our analysis of CMP's residential sales forecast. We have evaluated the economic theory underlying CMP's regression equations and whether alternative mathematical specifications of relationships between economic factors and sales – different variable definitions, mathematical transformations and autocorrelation adjustments – are appropriate. We have also analyzed each of the variables that CMP uses in its regression analysis – price levels, aggregate income, air conditioning saturation, and weather. The next section addresses variables that CMP did not include in its regression analysis including historic DSM, space heat usage and the final section presents our final baseline forecast and sensitivity analysis of the forecast.

The discussion of CMP's regression equation is organized by first explaining our process for benchmarking to the CMP forecast of use per customer and the number of customers. Next, we describe our analysis of the factors used in CMP's analysis beginning with the customer growth analysis and then moving to the income variable, the price variable and variables intended to reflect the effect of weather on sales.

Benchmarking to CMP

The first step of our analysis was to use the data provided by CMP and then to replicate their regression equations and their forecasts. This part of the analysis is important both because it confirms that CMP's statistical analysis is valid and because it assures that when we change a variable in the analysis, that our adjustment to the forecast is indeed the result of that change and not the result of a different underlying statistical

procedure. We have benchmarked both CMP's residential use per customer equation and the equation for customer growth equation. Matching the CMP equations is made somewhat complicated because of the presence of autocorrelation in the data. This means one cannot simply use the CMP data and plug it into a regression package, but that the method for adjusting the data to correct for autocorrelation must also be factored in.

In constructing our benchmarking analysis we attempted to match CMP's autocorrelation adjustments and its forecasts as well as the coefficients in the regression equations. When using CMP's autocorrelation factor, we were able to closely match both the coefficients ant the t-statistics that the Company presented in its testimony as shown in the table below.

Benchmarking of CMP Residential Equations

	CMP		Replication	
Variable	Coefficient	t-Stat	Coefficient	t-Stat
LogRPOE	(0.27026)	-5.19	(0.27026)	-5.28
LogRYP_YRCUST	0.25586	2.32	0.25586	2.41
HDD	0.00009	9.20	0.00009	9.29
THICDD	0.00015	2.42	0.00015	2.44
LogACTREND	0.06640	1.79	0.06640	2.05
ICESTORM	(0.04620)	-3.13	(0.04620)	-3.15
DUMMY3	0.32478	2.27	0.32479	3.62
_CONST	5.14563	9.69	5.12970	
_AUTO	0.94152	36.47	0.94152	

When we made a forecast with the above parameters, our forecast was virtually identical to CMP's forecast which confirms that our comparisons below are not distorted by different statistical techniques. When we computed the autocorrelation factor from the regression equation residuals rather than entering the value used by CMP, we developed a slightly different factor (.9021 versus .9415.) The small difference in the autocorrelation estimate had a minimal effect on the ultimate regression forecast. In

replicating the CMP results, we did confirm that CMP's equation in fact closely fit the historic data.

CMP uses a separate regression analysis to forecast the number of customers and we have attempted to match that equation as well as the use per customer equation. As with the customer use equation, the coefficients and our forecasting results were very close to the results presented by the Company. (In the case of the customer equation, we replicated the CMP autocorrelation factor.) The comparison of regression coefficients is shown on the table below.

Benchark of Customer Equation				
	CMP		Replication	
	Coefficient	t-Statistic	Coefficient	t-Statistic
Gains -1	0.796	21.762	0.796	21.92
Starts	0.172	6.015	0.172	6.07
Const	0.239	1.761	0.239	1.771
Auto - 4	(0.413)	(3.552)	(0.409)	(3.564)

Income Variable in the Residential Use per Customer Forecast

We begin the discussion of how we have investigated alternative variables by describing the income variable in CMP's analysis. In analyzing CMP's approach to modeling income we have done the following:

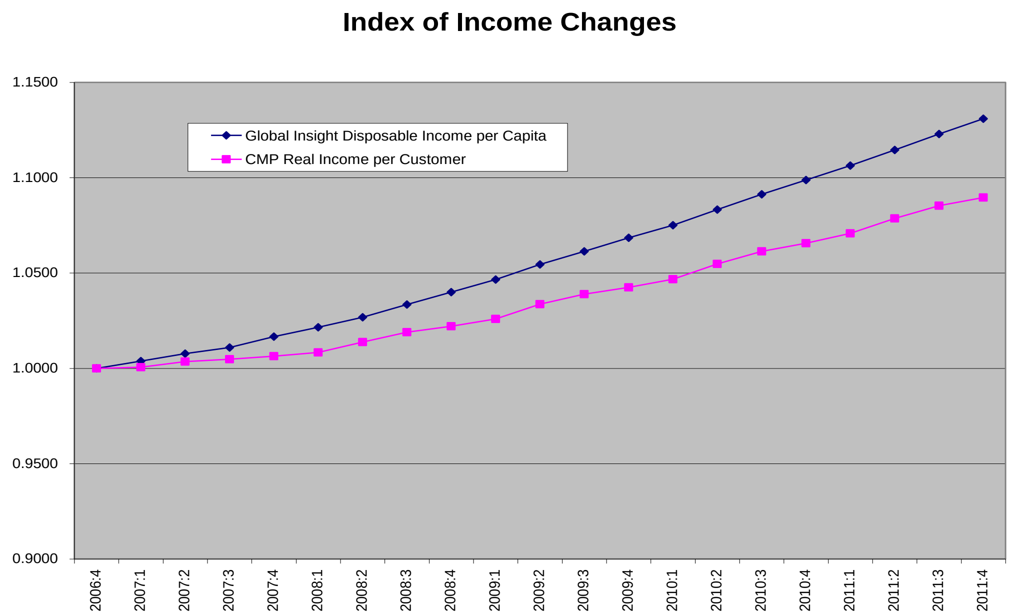
- Reviewed how CMP incorporates income in the forecasting analysis;
- Compared CMP's approach with the method used by some other utility companies;

- Recommended an alternative approach to incorporating income in the regression analysis which directly uses the Global Insight disposable income per capita rather than the manipulated variable that CMP creates.

CMP Approach to Modeling the Effects of Income

CMP gauges the effect of changes in housing size, size of appliances and many other factors on residential sales through including a variable that measures how much income the average customer earns for each period. The ultimate source of the historic income per customer and the projected income per customer data that CMP uses is disposable income in Maine published by Global Insight.[1] Although CMP discusses the Global Insight income projection, the Company in fact does not directly use the Global Insight data for Maine disposable income per capita in its regression analysis. Instead, the Company adjusts the Global Insight data to derive a variable which it names real income per customer. The graph below shows that CMP's income variable ultimately produces a lower forecast of income than the Global Insight per capita income. The graph demonstrates that from the first forecast year of 2007 through the year 2011, CMP's income variable grows by somewhat less than 15% if the Global Insight disposable income per capita is used while it grows by about 10% if the CMP adjusted variable is used.

[1] CMP defends the use of Global Insight as a source for measuring income through comparing it to three other forecasts. However, CMP makes the comparison in nominal terms rather than real terms. In real terms, the Global Insight forecast is lower than the forecast of the State Planning Office by .92% in 2007 and 2008.



Modeling of Income by Other Utility Companies

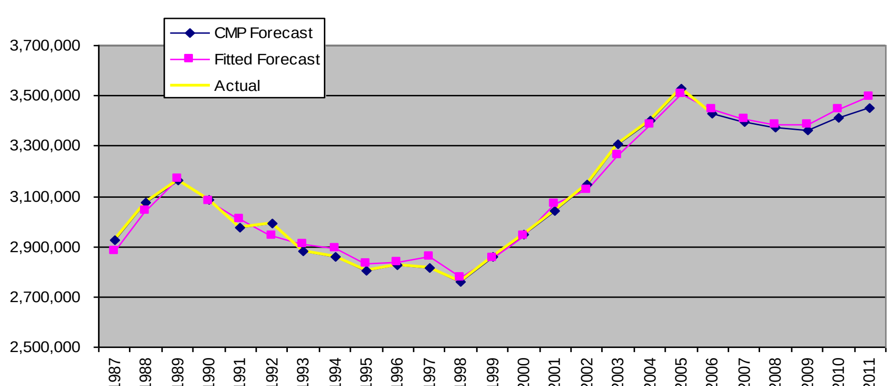
In evaluating whether CMP's approach of adjusting disposable income per capita is appropriate we have reviewed some information with respect to sales forecasting techniques used by other utility companies. In their recent case, Bangor Hydro used real per capita income projected Moodys.com and did not manipulate the data further. CMP's approach is also not consistent with forecasting techniques used by New York electric utilities that are subsidiaries of Energy East. According to a data request response provided by CMP, the New York electric companies use Moodys.com as does Bangor Hydro and the documents did not describe any adjustments to the income variable (the New York gas companies do not use an income variable.)

Recommended Approach to Modeling Income

We recommend directly using the Global Insight income per capita variable rather than the variable manipulated by CMP. It is not logical that the income divided by customers should grow at a significantly different rate than income per customer. Even if a justification could be made for CMP's approach on a prospective basis, the use of income per capita to establish relationships between use per customer and income would account for any historic difference. At best, CMP's approach does not add anything to the quality of the forecast. At worst, manipulation of the income variable biases the forecast.

Directly using the Global Insight income per capital variable produces a higher forecast than an equation which uses CMP's income definition. This is illustrated in the graph below. The graph uses all of the CMP variables and econometric techniques except for the income variable. When the Global Insight income per capita is directly used, the income elasticity increases, the t-statistic on the income variable changes and the R-squared of the regression increases.

Forecast Log Use per Customer
Versus Log Price Lag 4 and Log of Global Insight and others



When the Global Insight variable is substituted for the CMP variable, the forecast of use per customer increases as shown on the right part of the graph above. Relative to the CMP forecast, use of the alternative variable increases the forecast by 0.21%, 0.46%, 0.72%, .95% and 1.21% for the years 2007, 2008, 2009, 2010 and 2011.

Price Variable in Residential Use per Customer Forecast

The manner in which price elasticity is reflected in the residential forecast is an important issue in this case because of the sharp increases in energy prices that occurred in the past couple of years. When lagged prices are used in the regression equation to compute price elasticity, sales forecasts are reduced because the increases in 2006 price effect the forecast in 2007. We address many of the theoretical issues with respect to price elasticity in the appendix. The discussion in this section below focuses on the following practical issues:

- A review of CMP's approach.
- A discussion of the approach to computing price elasticity used by other utilities and BHE.
- A description of statistical problems with price elasticity measurement that occur because the level of historic sales affects prices.
- A summary of our recommendation with respect to price elasticity.

Review of CMP's Price Elasticity Approach

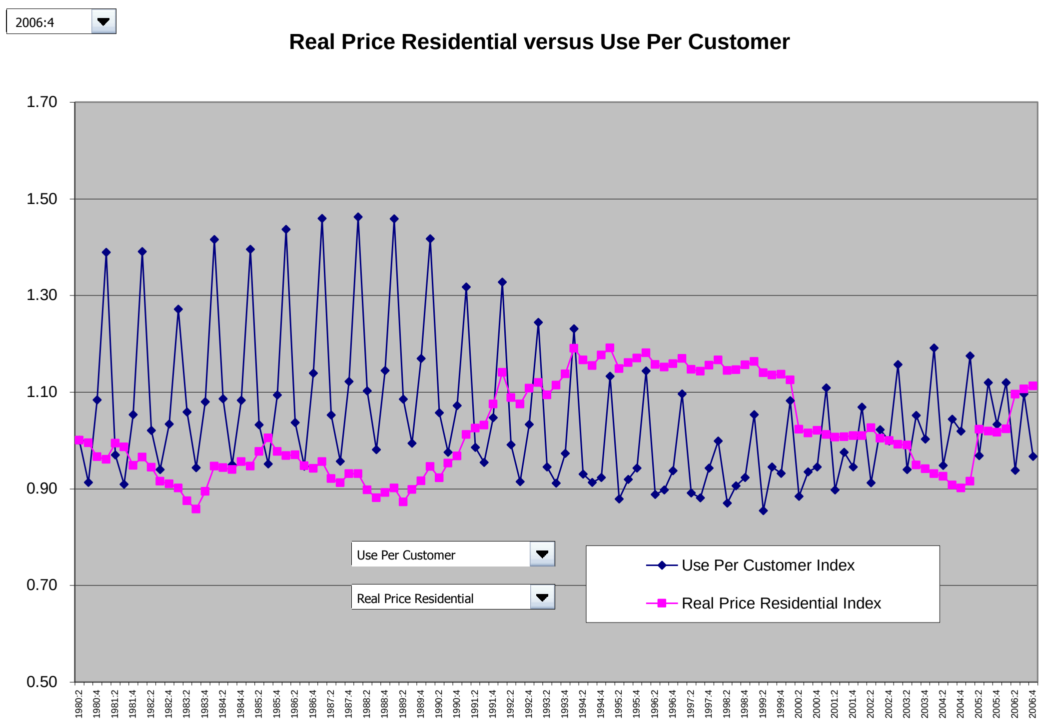
CMP uses the historic relationship between sales and lagged prices to conclude that the price elasticity is -.27. This means the when the real price increases by 10%, sales will decline by 2.7%. Given that prices increased in 2006 and CMP uses lagged prices in modeling price elasticity, a high price elasticity parameter aggrivates the effect. The high value of the price elasticity parameter combined with the high 2006 prices implies that alternative techniques for modeling price elasticity can have a large effect on the sales forecast. The table below shows that CMP's price elasticity parameter is higher than its price elasticity parameter in prior cases and is higher than the average price elasticity tabulated in a survey of electricity utility companies.

Alternative Residential Price Elasticity Parameters	
CMP Price Elasticity Estimate	-0.270
CMP Price Elasticty Forecast in 2005 Equation	-0.174
CMP Price Elasticty Forecast in 2004 Equation	-0.269
Average Price Elasticity in Utility Survey	-0.150

The theory underlying price elasticity is that there is some inherent true parameter which measures the manner in which consumers change their consumption when prices change. If this theory is valid and such a true parameter exists, then a robust regression equation would not result in a price elasticity parameter of -.27 this year and a parameter of -.174 last year.

The graph below illustrates why the price elasticity parameter measured by CMP is quite high as prices increased along with the decreased sales in the mid 1990's and then sales increased after the prices declined around the year 2000. The price increases

shown on the right hand side of the graph are important for the forecast. By assuming that sales are a function of lagged prices, those 2006 price increases shown at the end of the graph cause sales to decline in 2007.



Although the graph does show that sales generally when down when prices increased and that sales increased with lower prices, the graph does not prove cause and effect. Before deregulation, a decline in sales would cause revenue per kWh to increase to the extent that revenue requirements were fixed. This implies that sales changes could cause price changes rather than price changes causing sales variation. Further it is possible the sales changes happened to occur when prices changed and the effect could be random.

Price Elasticity Techniques Used by Other Utility Companies

CMP's approach to modeling price elasticity by assuming that consumers will wait one year when reacting to prices is not consistent with the manner in which other utilities construct econometric equations for forecasting sales. This is confirmed by the following:

- CMP provided a survey of the techniques used by utility companies in making price forecasts. In this survey, there were a series of questions regarding price elasticity and lags. The questions addressed whether utilities used current prices, prices with a one month lag or the moving average of prices. There was no survey question that addressed the possibility of using only a full year lag and no current price variable.
- In the survey provided by CMP, most of utility companies in the U.S. that responded used either current prices that are not lagged or prices lagged by one month.
- The sales forecast developed by BHE applies average prices in the past four quarters rather than lagged prices.
- In the information CMP provided about other Energy East companies, there was no indication that the companies used a lag of one year in computing price elasticity.

Statistical Issues in Measuring Price Elasticity

A basic assumption when constructing an econometric model is that independent variables such as price change because of changes in the dependent variable (residential

energy use). As stated above, in the case of residential energy sales, when sales decline, the revenue requirement formula causes average price increases putting into question the cause and effect that is a basic proposition when developing regression analysis. This problem which is known as simultaneity causes the price elasticity parameter to be biased. We do not suggest eliminating the price variable from the regression equation or developing an alternative statistical approach. However, the statistical problem means that one should be cautious in interpreting the price elasticity parameter.

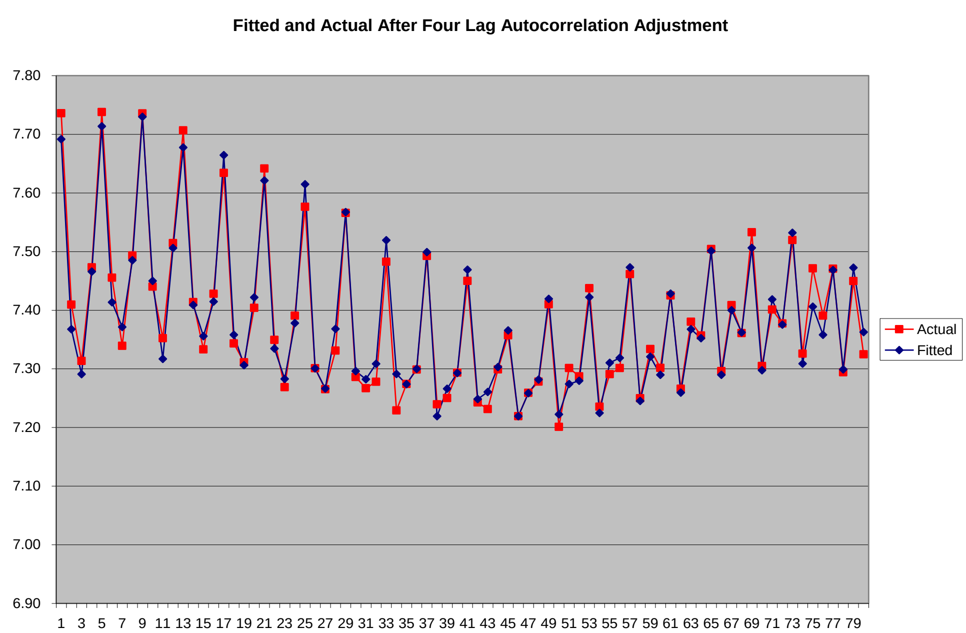
Residential Price Forecast

The effect of prices on sales projections depends on assumptions about the future price of electricity as well as the price elasticity parameter. CMP projects the real residential price to decline mainly because stranded investment charges are reduced (from 2007 through 2011 stranded investment charges are projected to decline by 75%.) The decline in stranded investment charges is tempered by an increase in transmission rates which are projected to increase by 25% over the 2007 through 2011 period. Distribution prices are projected not to change from a revision in baseline rates and then to change from inflation assumptions and the .5% proposed productivity offset. Finally, supply charges are projected to increase by 2.7% derived from forward prices published by NYMEX.

We have evaluated CMP's prices and with the exception of distribution prices we find their assumptions reasonable. In the case of distribution prices, we have assumed a 10% reduction in baseline rates and then a 1.75% productivity factor. This reduces overall prices by as much as 4% relative to the CMP projections.

Recommended Approach to Incorporate Price Elasticity in the Sales Forecast

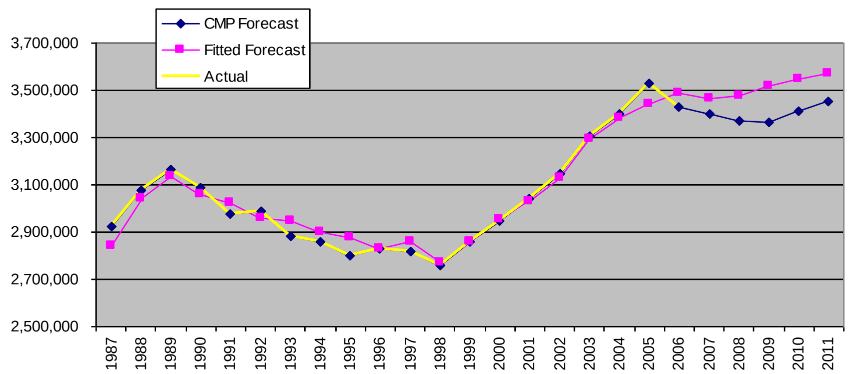
Given the discussion above we recommend that the price elasticity parameter and the sales forecast use current prices rather than lagged prices. When current prices are used rather than lagged prices, the elasticity coefficient declines from the -.27 to -.114. Further, the R-squared of the regression declines and the actual data are somewhat above the fitted data for the year 2005 as shown in the graph below. The fact that a somewhat better fit to historic data occurs through use of a four quarter lag does not justify use of a variable that is not logical. The section below includes a detailed discussion of why CMP's approach of searching for variables that fit historic data is inappropriate even if it results in a slightly higher t-statistic and R-squared.



Keeping all variables except price the same as those proposed by CMP and replacing the lagged price variable with the current price results in sales that increase

relative to CMP's forecast by 1.98%, 3.02%, 4.22%, 3.41%, and 2.92% for 2007, 2008, 2009, 2010 and 2011. When the alternative distribution prices as well as the elasticity are incorporated in the analysis, the sales forecast is 1.98%, 3.20%, 4.61%, 3.85% and 3.43% above the CMP forecast for the years 2007 to 2011. The effect of using current prices rather than lagged prices on fitted data and the forecast is shown on the graph below.

Forecast Log Use per Customer
Versus Log Alt Real Price and Log of CMP Income per Customer and others



Weather Variables in Residential Use per Customer Forecast

Besides price and income, the principal other factor that CMP uses in its equation are variables to represent weather. CMP includes heating degree day and humidity adjusted cooling degree day variables to represent the weather in its econometric analysis and it assumes that the average conditions in the past fifteen years represent future weather conditions. Other than its adjustment for humidity, CMP's approach to reflecting normal weather in the forecast is consistent with the method used by other companies. Our recommendation with respect to weather variables is to use unadjusted cooling degree days rather than cooling degree days adjusted for humidity. We do not

make adjustments to the weather data for different cut-off points or make adjustments for global warming.

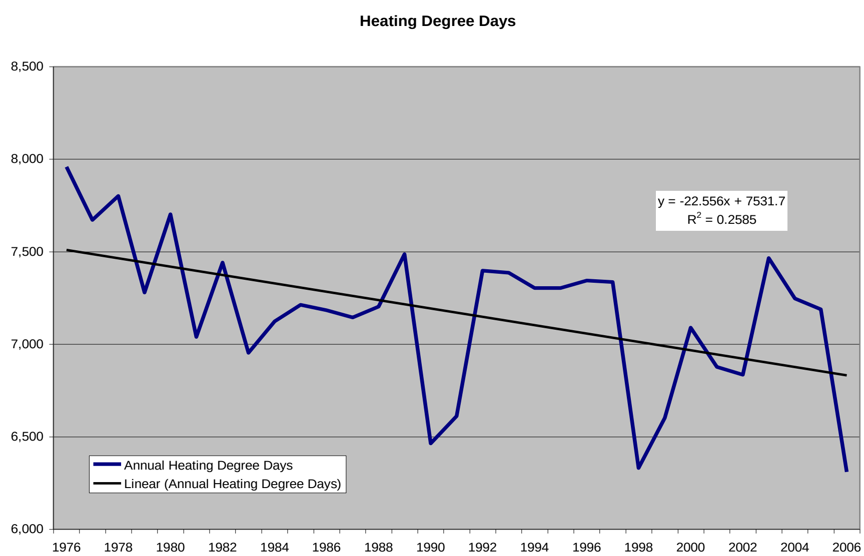
The remainder of this section discusses our observations with respect to CMP's weather modeling. Our first observation with respect to CMP's incorporation of weather in its models is that the Company's adjustment to include humidity as well as temperature in the cooling degree day calculations does not fit the historic data as well as the cooling degree days without adjustment. Our second observation is that since heating and cooling degree days are calibrated to 65 degrees Fahrenheit, the variables are not ideal representations of how weather affects sales. Our third observation is that the heating and cooling degree day series exhibits trends that reflect global warming, implying that use of the fifteen year average is not a good representation of normal weather.

CMP makes an adjustment to cooling degree days to incorporate humidity as well as temperature in the variable. The humidity adjusted variable is named THICDD while the unadjusted variable is called CDD. Since humidity affects the way consumers use air conditioners, one would expect adjusted variable THICDD to fit the historic data better than the unadjusted CDD cooling degree day variable. This however is not the case. If the variable without the humidity adjustment is substituted for the CMP adjusted variable, the t-statistic is higher and the sales forecast increases. Specifically, relative to the CMP forecast, use of the CDD variable instead of the THICDD variable increases the projection of residential use by .21% to .47%.

Cooling degree days and heating degree days are computed adding up the differences between each day's average temperature and 65°F. This measure is not necessarily the best measure of how weather affects electricity sales because people most

probably do not begin using their air conditioner until the temperature is higher than 65 °F and they do not begin using their space heaters until the temperature is colder than 65 °F. These problems mean that the weather variables contain an “error in variables” problem that makes interpretation of the regression equations problematic. This issue is discussed in more detail later in the Appendix.

In reviewing the weather variables it is apparent that heating degree days have declined implying warmer winters and cooling degree days have increased suggesting warmer summers. The downward trend in heating degree days is illustrated in the graph below. While it would be reasonable to use shorter periods or trends in projecting the heating and cooling degree day variables, the effect of warmer winters offset warmer summers and such adjustments would probably not have much effect on the ultimate forecast. Further, the heating and cooling degree day are not ideal in measuring the effect of weather on sales and incorporating heating degree days would imply a level of accuracy that is not present.



Forecast of Number of Residential Customers

Once the use per customer is developed, the number of customers is multiplied by the use per customer to project total residential sales. We discuss our review of CMP's residential customer forecast in the paragraphs below. Our conclusion is that the overall structure of CMP's econometric equation is reasonable, but that additional time periods should be used and lagged housing starts should be used instead of current housing starts. This recommendation produces a small increase in the number of customers. Our discussion of the number of customer analysis is separated into the following:

- Review of CMP's approach to forecasting customers
- Evaluation of CMP's approach compared to the method used by some other utility companies
- Analysis of alternative specifications for the customer regression equation
- Summary of the alternative recommended equation.

CMP's Approach to Forecasting Customers

CMP has created an equation for the change in customers compared to a year earlier which it names customer gains. CMP projects the number of customers on a quarterly basis which means the gains are computed as the difference between the number of customers for the current quarter and the number of customers four quarters ago. The Company projects the customer gains as a function of the one quarter lagged customer gains and the number of housing starts in the quarter. The variable which dominates the equation is the number of gains in the prior quarter. This approach amounts to assuming that the number of customer gains follows a moving average

process by which future gains depend on the number of historic gains with a slight effect of housing starts.

In developing the customer gains equation, CMP uses a different time period from the time period it uses in developing the customer use equation. For customer use, the Company estimates the equation beginning with data in 1986. In contrast, the customer equation is estimated using a time period beginning in 1990. While this may seem to be a minor point, CMP's method ignores large swings in customer additions that occurred before 1990 and provide valuable information in estimating an equation.

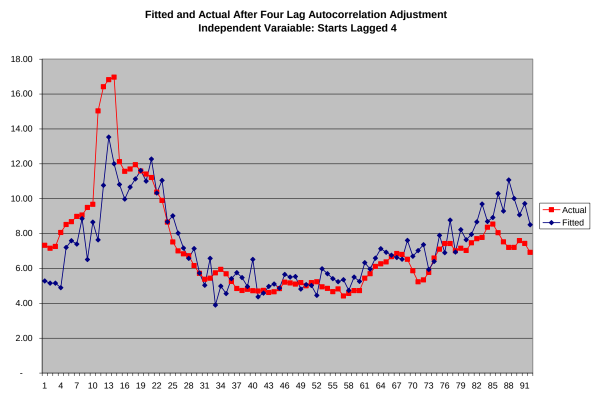
Customer Forecasts made by Other Utility Companies

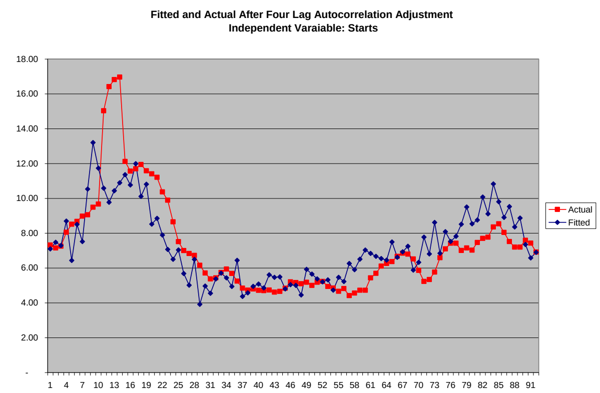
CMP's approach to projecting customer growth is not the same as some other utility companies for which we have information. BHE for example simply computes the historic trend in customer growth. If CMP used this approach, forecast would be higher as CMP's forecast is influenced by declines in the number of housing starts projected by Global Insight. Some of the other Energy East companies use exponential smoothing which is similar to trend analysis and does not incorporate information about the number of housing starts. Other Energy East companies use the number of households as the primary driver variable, but they do not appear to develop models from changes in the number customers as does CMP. Although CMP's approach differs from the techniques used by other companies, we find the overall method reasonable as it incorporates both trending through inclusion of the lagged dependent variable as well as information about future housing starts.

Alternative Specifications for Customer Growth

We have analyzed CMP's customer equation through investigating a number of alternative possible specifications. These specifications include not using a lagged dependent variable; performing the analysis on the number of customers directly rather than the changes in the number of customers; using lagged housing starts rather than current housing starts; not including an autocorrelation factor; and, using different independent variables including dummy variables.

To evaluate how variables affect the customer gains we removed the lagged dependent variable and we use a longer time period than the time frame used by CMP. When we evaluated equations that are derived from the number of customers instead of customer changes and tested how population or households rather affected the equation. These equations had very high R-squared of more than 99%, but they also had high autocorrelation. This implies that it is reasonable to perform the analysis using gains rather than the number of customers. In modeling the customer gains variable, the number of housing starts was more significant than other variables that we investigated. However, a variable measuring the lagged customer starts produces a better fit than the use of current starts. The two graphs below show relationship between fitted and actual data when current starts are used and lagged current starts are used. By comparing these two graphs in the early periods when there were large swings, one can see that lagged housing starts represent the data better than current housing starts.

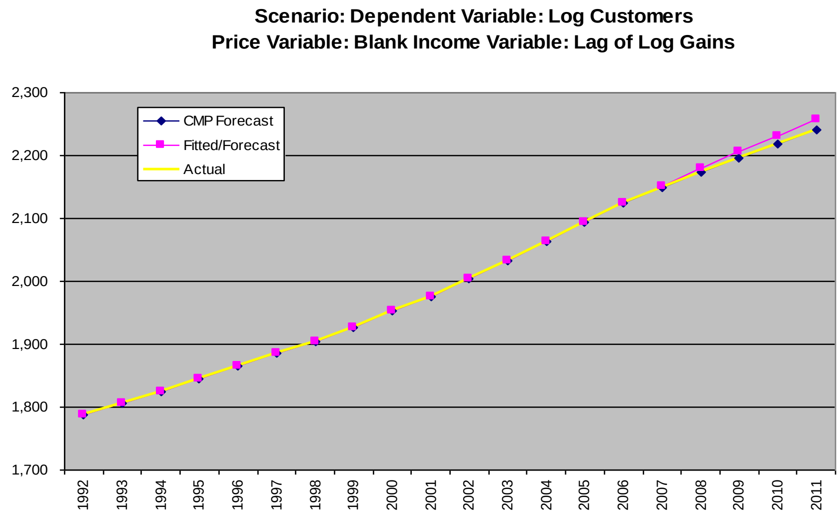




Recommended Forecast for Residential Customers

We recommend that the equation for computing the number of new customers use lagged housing starts and dummy variables for the ice storm and different quarters. Further, the equation should be estimated from data beginning in 1982 instead of 1990. Use of lagged housing starts rather than current housing starts is logical since there is a lag between the commencement of construction on a new home and the completion of construction when a new customer is recorded by CMP.

The alternate regression results in somewhat higher coefficients for both lagged customer gains and for lagged housing starts. The forecasted number of customers relative to the CMP forecast is shown in the graph below. Application of the alternative equation increases the number of new customers by 0.14%, 0.30%, 0.43%, 0.54% and 0.66% in 2007, 2008, 2009, 2010 and 2011.



4. VARIABLES OMITTED FROM CMP'S RESIDENTIAL SALES EQUATION

In this part of the analysis we discuss variables that were not included in the CMP regression equation of customer use. Statistical and forecasting problems that arise from omitted variables are described in the Appendix. The variables that CMP omitted and that we explicitly consider include historic energy savings from DSM and changes in space heat usage. There are other variables omitted variables in the CMP equation such as the average size of the housing stock and the number of vacation homes. However we did not have sufficient data to include these variables in the regression equation.

Omitted Demand Side Management Programs

CMP accounts for the DSM programs administered by Efficiency Maine in its forecasts through subtracting the estimated future incremental savings from the forecast it developed from econometric equations. We agree that programs administered by

Efficiency Maine affect CMP's sales forecast as the objective of the programs is obviously to save energy. However, because the approach ignores programs administered by CMP and programs administered Efficiency Maine, there is a bias in the forecast. The discussion below addresses the issue of how omission of historic DSM affects the regression equation and the forecast of use per customer. The discussion is divided into the following subjects:

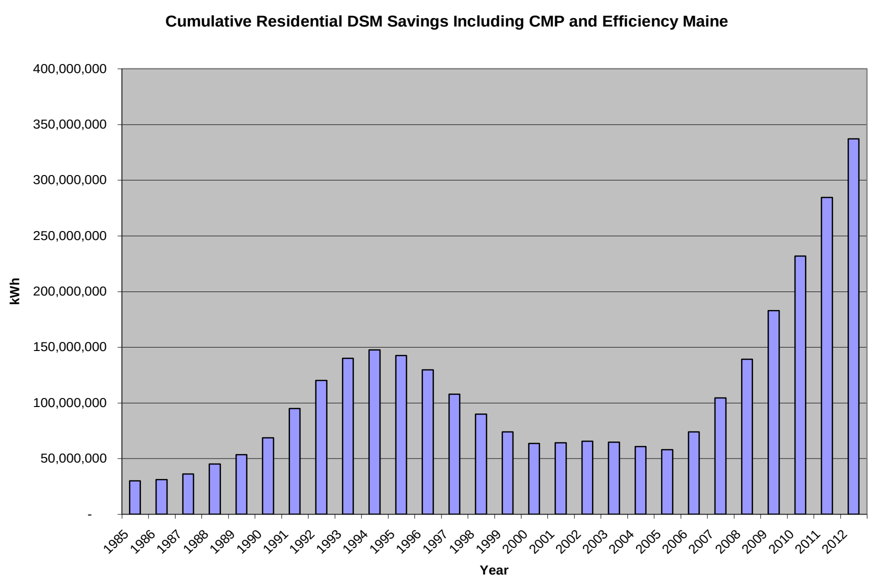
- Compilation of historic DSM data
- Incorporation of historic DSM in the regression equations
- Implications of including historic DSM programs on the regression equation and the forecast

Historic DSM Data

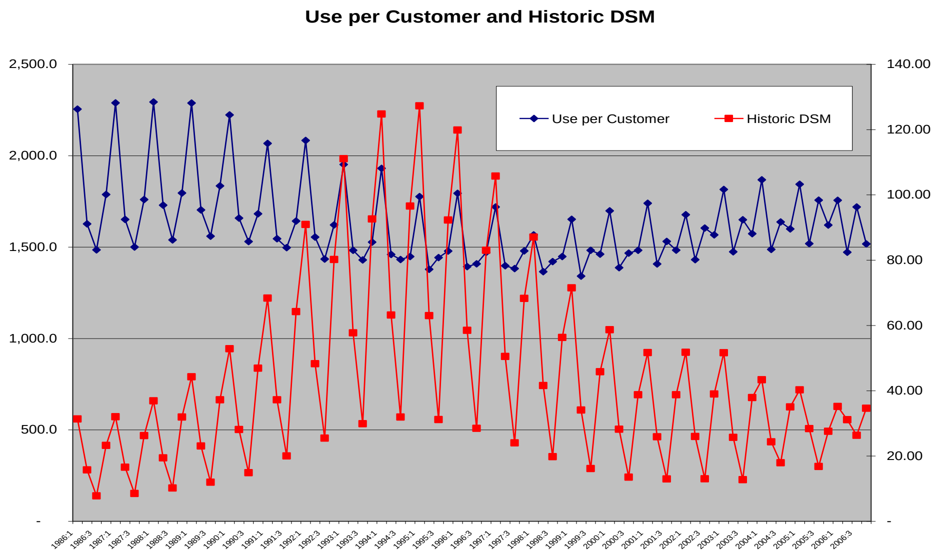
When evaluating the effect of the omitted DSM savings on the regression equation, it is the energy savings that are important to consider, whether the energy savings came from programs administered by CMP itself of by Efficiency Maine. Further, the effect of expiring DSM savings must be reflected as well as the incremental new savings. To incorporate the historic DSM and the expiring DSM savings, we have created a data series that includes accumulated residential DSM savings arising from programs administered by the Company since 1985, the accumulated savings resulting from Efficiency Maine programs since 2003, and expiring savings from the programs. The expiring savings are computed through assuming programs have a life of six years. The source of the savings data prior to 1995 is from reports filed by CMP to the Commission; the source of subsequent savings from DSM programs is a data response

provided by CMP and the source of Efficiency Maine savings is the cumulative DSM savings used by CMP in its update.

The accumulated DSM resulting from this analysis is shown in the graph below. The graph demonstrates that historic DSM programs peaked in the mid 1990's and then have declined. The Efficiency Maine programs eventually will accumulate to more than the historic DSM programs by the year 2010. To incorporate the DSM savings in the regression analysis, the annual DSM savings are allocated to quarters.



The graph below shows both the historic DSM programs and the CMP residential use per customer. This graph demonstrates that use per customer declined when DSM programs were high as expected. This implies that it may the DSM programs as well as the price, income or weather that are affecting the energy usage. If the DSM programs are ignored in the analysis, then estimates of coefficients for price income and weather will be biased.



Incorporation of Historic DSM in Regression Analysis

The historic DSM programs could be included as an independent variable in the regression equation. If this were done, one would expect that the coefficient of DSM per customer should be -1.0 as there should be a one for one relationship between energy savings and ultimate energy use. If this approach were used, the forecasted DSM would be modeled through plugging the DSM forecast into the regression equation as is the case with the income and price variable. We have run a regression equation where use per customer is the dependent variable and DSM is only independent variable. In this case, the coefficient on DSM is even higher in absolute value than 1.0. However, when other variables are added to the equation, the correlation between DSM savings and other variables the absolute value of the coefficient is reduced.

An alternative approach we adopt is to constrain the coefficient of DSM savings to -1.0 through adding the DSM savings per customer to the use per customer and then

running the regression on a pre-DSM basis. This is accomplished through the following three step process:

Step 1: Add the historic DSM per customer to the residential use per customer in the historic time period used to estimate the regression equation

Step 2: Run regression analysis using pre-DSM customer use

Step 3: Subtract total DSM from the fitted values and projected values generated by the pre-DSM residential use regression equation.

We have applied this approach since it is reasonable to expect that energy savings from DSM programs have a one for one effect on customer use.

Incorporation of Historic DSM in Regression Analysis

When historic DSM is added to customer use, the forecast of customer use changes because regression coefficients are different and because the projected DSM incorporates expiration of historic DSM programs. To illustrate the effect of omitting the DSM variable, we have evaluated how the DSM approach above affects the forecast without making any of the other adjustments to the CMP forecast discussed above (i.e. no price elasticity, income, or weather effect.) When historic DSM is added to customer use, ~~the regression equation has a higher R-squared and results~~ there is ~~in~~ an increased forecast of customer use as shown in the table below:

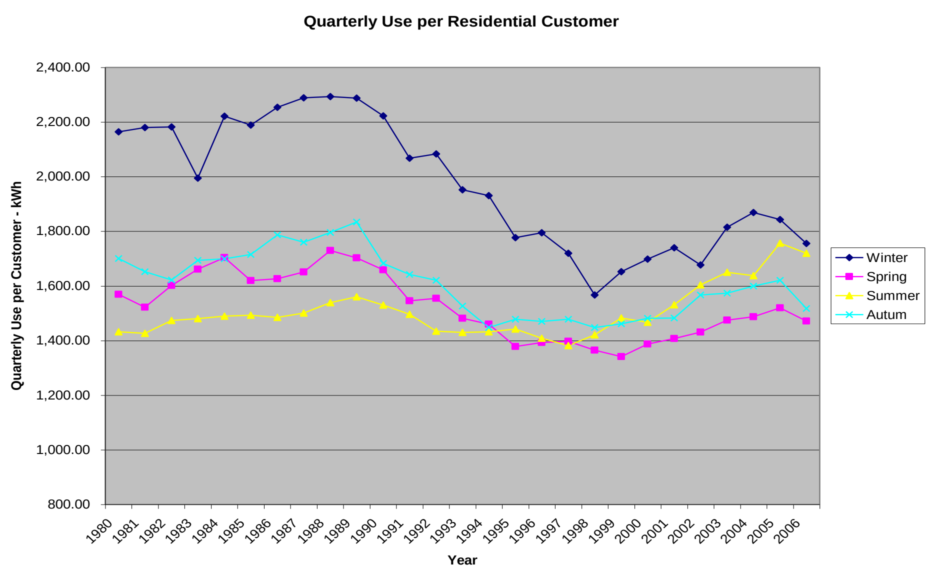
DSM Effect	
Year	Pct vs CMP
~~2007~~	~~1.89%~~
2008	1.94%
2009	2.17%
2010	2.75%
2011	3.25%

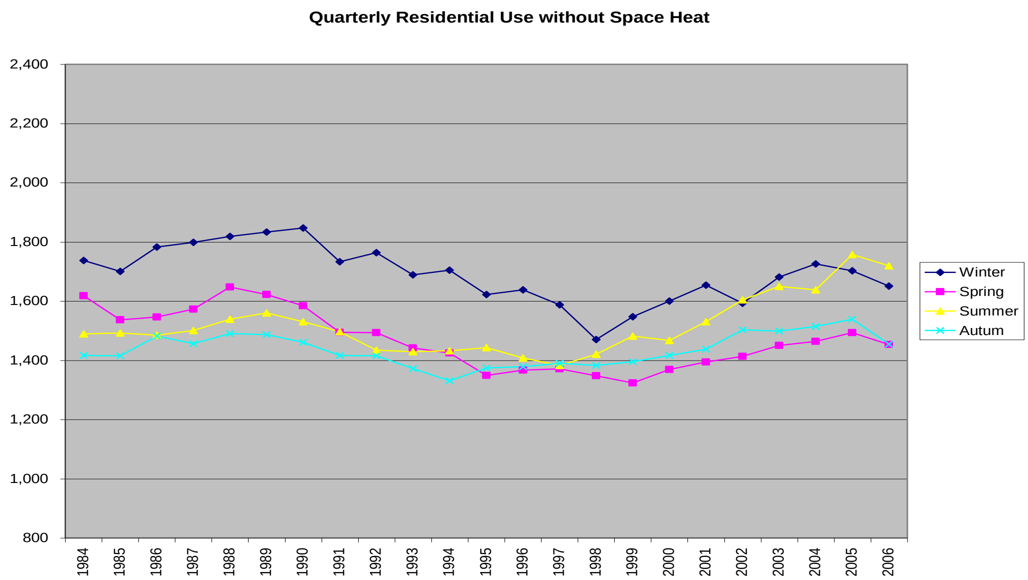
2007	1.05%
2008	1.30%
2009	1.43%
2010	1.25%
2011	1.03%

The ultimate effect of the DSM programs on the baseline forecast is discussed below in the sensitivity analysis section.

Omitted Space Heat Variable

Changes in electric space heat have had a large effect on CMP's historic sales because of the relative cost of electric and other sources of heat, new technologies and other factors. These factors are not included in CMP's econometric analysis implying that the equation has an omitted variable problem. The effect of changes in space heat and water heat are shown on the two graphs below. The first graph includes space heat while the second graph excludes space heat load. The space heat load is derived from data provided by CMP.





The two graphs above illustrate that the trends in residential sales change significantly when space heat is removed. As with DSM, the omission of space heat changes can affect the regression equation because space heat effects are attributed to other variables. When space heat is include in the regression equation, the coefficient is positive as expected and the ultimate forecast of sales increases. Alternatively, the space heat use can be constrained to have a one to one effect on sales. When this method is applied, the regression equation is made without space heat and then space heat sales are separately added to the forecast that results from the regression equation. This approach has a relatively small effect on the forecast.

5. FINAL BASELINE EQUATION AND SENSITIVITY ANALYSIS

In this part of the report we present our final recommended residential equation and sensitivity analysis on the regression equation. While the baseline forecast that we present contains our preferred forecast, we recognize that selection of some of the

variables is subject to judgment and that alternative regression equations may be reasonable. The sensitivity analysis demonstrates that alternative reasonable equations produce forecasts that are similar or higher than our recommended forecast. This confirms that our forecast is reasonable.

Summary of Residential Baseline Forecast

The baseline residential sales forecast we recommend incorporates inclusion of the space heat, historic DSM, current rather than lagged prices, alternative distribution price forecasts, corrected income and alternative customer forecasts. In addition, the baseline equation does not include air conditioning saturation. Even though the air conditioning saturation variable increases the forecast, we have excluded it because of statistical problems. First, since the air conditioning saturation variable is closely correlated with the income variable it affects the significance of the other variables. Second the air conditioning variable contains errors in variables problems and the variable was not forecast on an objective basis.

After changing the CMP independent and dependent variables, the resulting regression is presented below. In this equation the t-statistics for the price variable and the income variable are somewhat below 2.0 whereas the t-statistics were above 2.0 in CMP's regression. The lower t-statistics result in part because there is less variation in the customer use variable when space heat is excluded from customer use.

Coefficients and t-Stasticis in Final Regression

	Coefficient	t-Stat
Log Alt Real Price	(0.09325)	-1.66
Log of Global Insight	0.16948	1.35
HDD	0.00005	4.12
CDD	0.00015	3.45
Ice Storm Dummy	(0.04709)	-2.76
First Quarter Dummy	0.08811	1.52
Second Quarter Dummy	0.02764	0.47
Third Quarter Dummy	0.13753	2.17

When space heat is left in the customer use definition, the coefficients are more significant as shown in the table below. This equation produces a forecast that is significantly higher than our baseline recommendation.

Coefficients and t-Stasticis in Final Regression

	Coefficient	t-Stat
Log Alt Real Price	(0.15092)	-2.15
Log of Global Insight	0.35828	2.26
HDD	0.00011	7.39
CDD	0.00017	3.23
Ice Storm Dummy	(0.04840)	-2.28
First Quarter Dummy	0.05073	0.67
Second Quarter Dummy	0.05215	0.69
Third Quarter Dummy	0.20496	2.50

Coefficients and t-Stasticis in Final Regression

	Coefficient	t-Stat
Log Alt Real Price	(0.10086)	-1.70
Log of Global Insight	0.26588	1.88
HDD	0.00008	6.70
CDD	0.00016	3.50
Ice Storm Dummy	(0.04560)	-2.60
First Quarter Dummy	0.05510	0.71
Second Quarter Dummy	0.04267	0.55
Third Quarter Dummy	0.19744	2.43

The final forecast involves developing an equation for the log of customer use without space heat and without historic DSM. This forecast must be converted from logs

and then space heat energy must be added and DSM must be reduced from the forecast. The table below summarizes components of the baseline forecast.

Forecast									
	Forecast LN Per Customer	Forecast Use per Customer	Number of Customers	Pre-DSM Pre-Space Heat Use	Space Heat Load Added	Sub-Total Before Adding DSM	Less: CMP DSM	Less: Historic DSM	Total Sales
2007	29.53	6,438.82	2,152.00	3,463,793	122,903.50	3,586,697	-	92,261	3,494,435
2008	29.53	6,448.27	2,179.60	3,513,398	122,334.91	3,635,733	-	125,343	3,510,390
2009	29.57	6,506.59	2,205.70	3,587,626	122,930.20	3,710,556	-	165,450	3,545,106
2010	29.60	6,554.40	2,231.31	3,655,947	124,274.11	3,780,221	-	212,290	3,567,932
2011	29.63	6,609.30	2,256.18	3,727,664	125,606.78	3,853,270	-	263,357	3,589,913

Sensitivity Analysis

In this section we present a sensitivity analysis that presents results of alternative variables and time periods. Some of the factors that we evaluate in the sensitivity analysis include:

- Leaving space heat in the regression analysis
- Using a price variable that is computed from the average of the prior four quarters rather than the current price
- Modeling DSM in the manner that CMP does rather than including historic DSM
- Including the Air Conditioning variable in the regression
- Not including dummy variables in the first and second quarter
- Using CMP projections of customer growth rather than the alternative number of customers

In addition to the above scenarios, we have included additional scenarios that include multiple changes in the variables. For each of the scenarios, we have evaluated

how the scenarios change if different time periods are used to estimate the regression equations. The alternative time periods either begin earlier in 1984 or later in 1990. The table shown in the introductory section demonstrates the sensitivity analysis using the time period applied by CMP. The tables below show alternative scenarios with different time periods. As with the sensitivity shown in the introduction, data that are shaded represent scenarios in which the sales forecast exceeds our base case scenario. The tables below along with the sensitivity table presented in the introductory section show that there are many alternative reasonable scenarios that generate an even higher forecast than our baseline forecast -confirming the baseline case is not unreasonably optimistic.

Residential Equation Scenario Analysis - 1990

Year	2007	2008	2009	2010	2011
Scenario					
CMP Case	0.74%	1.08%	1.26%	0.90%	0.62%
Baseline Case	**3.58%**	**5.06%**	**6.22%**	**5.40%**	**4.90%**
Scenario 1: Include Space Heat	4.72%	6.20%	7.50%	6.80%	6.47%
Scenario 2: Price Variable with Average of Four Quarters	2.97%	4.22%	5.48%	4.94%	4.59%
~~Scenario 3: CMP Modeling of DSM~~	~~4.72%~~	~~6.51%~~	~~7.67%~~	~~6.42%~~	~~5.26%~~
Scenario 4: Air Conditioning Variable Included	4.14%	5.94%	7.01%	5.97%	5.09%
Scenario 5: Exclude 1st and 2nd Dummies	3.56%	4.97%	6.00%	5.08%	4.47%
Scenario 6: CMP Customer Equation	3.44%	4.74%	5.77%	4.82%	4.19%
Scenario 7: Average Price and Include Space Heat	3.48%	4.41%	5.67%	5.22%	4.96%
Scenario 8: Average Price, Space Heat and CMP DSM	1.44%	2.34%	3.51%	3.03%	2.79%
Scenario 9: A/C, Average Price, Space Heat and CMP DSM	2.42%	3.82%	4.82%	3.90%	3.07%
Scenario 10: Space Heat and A/C Included	5.37%	7.23%	8.34%	7.20%	6.17%
Scenario 11: Space Heat and No Dummies	4.57%	6.01%	7.34%	6.65%	6.33%

Residential Equation Scenario Analysis - 1990

Year	2007	2008	2009	2010	2011
Scenario					
CMP Case	0.74%	1.08%	1.26%	0.90%	0.62%
Baseline Case	**3.58%**	**5.06%**	**6.22%**	**5.40%**	**4.90%**
Scenario 1: Include Space Heat	3.27%	4.67%	5.78%	4.90%	4.35%
Scenario 2: Price Variable with Average of Four Quarters	2.97%	4.22%	5.48%	4.94%	4.59%
Scenario 3: CMP Modeling of DSM	3.42%	5.13%	6.06%	4.72%	3.48%
Scenario 4: Air Conditioning Variable Included	4.14%	5.94%	7.01%	5.97%	5.09%
Scenario 5: Exclude 1st and 2nd Dummies	3.56%	4.97%	6.00%	5.08%	4.47%
Scenario 6: CMP Customer Equation	3.44%	4.74%	5.77%	4.82%	4.19%
Scenario 7: Average Price and Include Space Heat	2.45%	3.46%	4.52%	3.79%	3.26%
Scenario 8: Average Price, Space Heat and CMP DSM	1.44%	2.34%	3.51%	3.03%	2.79%
Scenario 9: A/C, Average Price, Space Heat and CMP DSM	2.42%	3.82%	4.82%	3.90%	3.07%
Scenario 10: Space Heat and A/C Included	3.98%	5.79%	6.76%	5.59%	4.54%
Scenario 11: Space Heat and No Dummies	3.24%	4.60%	5.61%	4.66%	4.02%

Residential Equation Scenario Analysis - 1984					
Year	2007	2008	2009	2010	2011
Scenario					
CMP Case	-0.17%	-0.25%	-0.27%	-0.18%	-0.10%
Baseline Case	**2.55%**	**3.70%**	**4.97%**	**3.99%**	**3.32%**
Scenario 1: Include Space Heat	4.33%	6.01%	8.31%	8.22%	8.53%
Scenario 2: Price Variable with Average of Four Quarters	1.70%	2.53%	3.76%	3.24%	2.78%
~~Scenario 3: CMP Modeling of DSM~~	~~3.78%~~	~~5.16%~~	~~7.32%~~	~~6.94%~~	~~6.92%~~
Scenario 4: Air Conditioning Variable Included	2.47%	3.64%	5.06%	4.11%	3.45%
Scenario 5: Exclude 1st and 2nd Dummies	2.67%	3.76%	4.96%	3.93%	3.21%
Scenario 6: CMP Customer Equation	2.41%	3.39%	4.52%	3.41%	2.62%
Scenario 7: Average Price and Include Space Heat	3.19%	4.43%	6.68%	7.28%	7.88%
Scenario 8: Average Price, Space Heat and CMP DSM	0.60%	1.46%	3.19%	3.34%	3.54%
Scenario 9: A/C, Average Price, Space Heat and CMP DSM	0.58%	1.45%	3.20%	3.37%	3.56%
Scenario 10: Space Heat and A/C Included	4.37%	6.18%	8.70%	8.73%	9.13%
Scenario 11: Space Heat and No Dummies	4.37%	6.05%	8.32%	8.22%	8.53%

Residential Equation Scenario Analysis - 1984					
Year	2007	2008	2009	2010	2011
Scenario					
CMP Case	-0.17%	-0.25%	-0.27%	-0.18%	-0.10%
Baseline Case	**2.55%**	**3.70%**	**4.97%**	**3.99%**	**3.32%**
Scenario 1: Include Space Heat	2.85%	4.34%	6.00%	5.39%	5.10%
Scenario 2: Price Variable with Average of Four Quarters	1.70%	2.53%	3.76%	3.24%	2.78%
Scenario 3: CMP Modeling of DSM	2.30%	3.54%	5.13%	4.29%	3.75%
Scenario 4: Air Conditioning Variable Included	2.47%	3.64%	5.06%	4.11%	3.45%
Scenario 5: Exclude 1st and 2nd Dummies	2.67%	3.76%	4.96%	3.93%	3.21%
Scenario 6: CMP Customer Equation	2.41%	3.39%	4.52%	3.41%	2.62%
Scenario 7: Average Price and Include Space Heat	1.82%	2.82%	4.39%	4.23%	4.07%
Scenario 8: Average Price, Space Heat and CMP DSM	0.60%	1.46%	3.19%	3.34%	3.54%
Scenario 9: A/C, Average Price, Space Heat and CMP DSM	0.58%	1.45%	3.20%	3.37%	3.56%
Scenario 10: Space Heat and A/C Included	2.86%	4.43%	6.29%	5.76%	5.53%
Scenario 11: Space Heat and No Dummies	2.82%	4.22%	5.86%	5.18%	4.82%